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Advancements in CNC Machine System for Enhanced Part Development

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ABSTRACT- This paper presents a comprehensive study on the part development of Aluminium-Silicon Carbide (AlSiC) Particle Metal Matrix Composite (MMC) using Computer Numerical Control (CNC) machining. AlSiC MMCs have gained significant attention due to their excellent mechanical properties and thermal conductivity, making them suitable for various applications in industries such as aerospace, automotive, and electronics. The objective of this research is to investigate the effects of CNC machining parameters, such as cutting speed, feed rate, and depth of cut, on the machinability and surface quality of AlSiC MMC parts. Additionally, the paper aims to optimize the CNC machining process to enhance the performance and dimensional accuracy of the machined parts.

KEYWORDS- Aluminium-Silicon Carbide (AlSiC) Particles , Metal Matrix Composite (MMC) , Computer Numerical Control (CNC) Machines, Design of Experiments (DOE) etc.

I. INTRODUCTION

Aluminium-Silicon Carbide (AlSiC) Particle Metal Matrix Composites (MMCs) have emerged as highly important materials in various engineering applications. The combination of aluminium and silicon carbide particles offers unique properties that make AlSiC MMCs desirable for a wide range of industries, including aerospace, automotive, and electronics.

A. Background and Significance of AlSiC MMCs in Engineering Applications

AlSiC MMCs possess exceptional mechanical properties, such as high strength, stiffness, and thermal conductivity. These characteristics make them suitable for applications where lightweight materials with excellent thermal management capabilities are required. The aerospace industry utilizes AlSiC MMCs in the construction of aircraft components, such as heat sinks, engine components, and electronic packaging, as they offer a balance between weight reduction and superior thermal dissipation.

In the automotive sector, AlSiC MMCs are used to manufacture brake systems, engine components, and power electronics modules. Their excellent thermal conductivity helps in dissipating heat efficiently, improving the overall performance and reliability of automotive systems. The electronics industry also benefits from AlSiC MMCs due to their high thermal conductivity and electrical insulation properties, which enable the development of compact and efficient electronic devices.

The unique combination of properties offered by AlSiC MMCs has led to their increasing popularity and widespread adoption in various engineering applications. As a result, there is a growing need for effective manufacturing processes to transform AlSiC MMCs into functional parts.

B. Overview of CNC Machining and its Role in Part Development

Computer Numerical Control (CNC) machining plays a pivotal role in the part development of AlSiC MMCs. CNC machining involves the use of computer-controlled machine tools to precisely shape and form materials according to specific design requirements. The automation and accuracy offered by CNC machining make it a preferred method for manufacturing complex and high-precision components.

In the context of AlSiC MMCs, CNC machining enables the production of parts with tight tolerances and superior surface quality. The CNC machines can be programmed to precisely control cutting parameters, such as cutting speed, feed rate, and depth of cut. Optimizing these parameters is crucial in achieving desired surface finish and dimensional accuracy in AlSiC MMC parts.

CNC machining allows for the efficient removal of excess material and the creation of intricate geometries, resulting in the production of high-quality AlSiC MMC components. The ability to control the machining parameters and processes ensures consistency and repeatability, enabling manufacturers to meet stringent design requirements.

By leveraging CNC machining in the part development of AlSiC MMCs, engineers and manufacturers can achieve improved functionality, performance, and reliability. The precise control and automation offered by CNC machining contribute to the production of complex AlSiC MMC components with enhanced thermal management capabilities.

In conclusion, the background and significance of AlSiC MMCs in engineering applications highlight their unique properties and increasing demand across various industries. The role of CNC machining in the part development process is crucial in achieving the desired dimensional accuracy, surface finish, and functionality of AlSiC MMC components. The combination of AlSiC MMCs and CNC machining techniques opens up new possibilities for advanced manufacturing and improved performance in diverse engineering applications.

II. LITERATURE REVIEW

A. Introduction

The field of CNC machine systems has witnessed remarkable progress, greatly influencing the development of parts using metal matrix composites (MMCs). Among these composites, aluminium silicon carbide (AlSiC) particles have emerged as a promising choice for various industrial applications. This literature review aims to provide an extensive overview of research conducted on CNC machine systems for enhanced part development with AlSiC particle MMCs. By examining 22 relevant references, this review covers topics such as surface roughness prediction, machining parameter optimization, drilling performance, tool wear analysis, and surface integrity. Through a comprehensive analysis of these studies, this review aims to contribute to the understanding of the advancements in CNC machine systems for AlSiC particle MMCs.

B. Surface Roughness Prediction and Optimization

The attainment of desired surface roughness is vital for achieving high-quality part development. **Zhang et al. (2020**) proposed a hybrid machine learning approach that effectively predicts and optimizes surface roughness in milling processes. By integrating various machine learning algorithms, this approach offers valuable insights for manufacturers, enabling them to enhance surface quality while ensuring improved efficiency and reduced costs.

C. Machining Parameter Optimization

Optimizing machining parameters is crucial for enhancing the overall performance of AlSiC MMCs. Chen et al. (2019) conducted an experimental investigation and optimization of machining parameters specifically for AlSiC composites. Through the application of statistical techniques and response surface methodology, this study emphasized the significance of identifying optimal parameters to enhance tool life, surface quality, and productivity during the machining process. The findings provide valuable guidance for manufacturers in making informed decisions to achieve efficient part development with AlSiC MMCs.

D. Drilling Performance

Drilling performance is a critical aspect to consider for successful part development. Li et al. (2018) conducted an experimental study on the drilling performance of carbon fiber-reinforced polymer (CFRP) composites. The research focused on factors such as drill wear, hole quality, and delamination, offering valuable insights into optimizing drilling processes for AlSiC MMCs. These findings contribute to the development of effective drilling strategies, ensuring accurate hole creation and minimizing workpiece damage.

E. Tool Wear and Surface Integrity

Tool wear and surface integrity are key considerations when machining MMCs. **Zhang et al. (2017)** investigated tool wear and surface integrity during high-speed milling of carbon fiber-reinforced plastics (CFRPs). The study analyzed the effects of milling parameters on tool wear, surface roughness, and delamination, enabling manufacturers to optimize the milling process and extend tool life. Understanding the mechanisms of tool wear and their impact on surface integrity is essential for manufacturers to implement preventive measures and select appropriate cutting tools, ensuring optimal part development with AlSiC MMCs.

F. Tool Life Prediction and Wear Mechanism

Understanding tool wear mechanisms and predicting tool life is crucial for efficient machining. **Yu et al. (2016)** studied tool life prediction and wear mechanisms of polycrystalline diamond (PCD) tools when cutting CFRPs. The research investigated the effects of cutting parameters, tool geometry, and material properties on tool wear, facilitating the selection of appropriate cutting tools and optimizing machining processes. Accurate tool life prediction allows manufacturers to plan tool replacements and minimize production interruptions, leading to cost savings and improved productivity.

G. Surface Roughness Optimization in End Milling

Surface roughness optimization poses a significant challenge in end milling of AlSiC MMCs. **Rahman et al. (2015)** proposed a modeling and optimization approach to improve surface roughness in end milling of AlSiC MMCs. The study focused on the selection of cutting parameters, tool geometry, and machining strategies to achieve the desired surface quality. The findings contribute to the development of efficient machining techniques, enabling manufacturers to enhance surface roughness control during the end milling process, ultimately improving part quality.

H. Cutting Forces and Tool Wear

Understanding cutting forces and tool wear is crucial for efficient machining. **Xie et al. (2014)** investigated cutting forces and tool wear during the machining of carbon fiber-reinforced plastics (CFRPs). The study analyzed the effects of cutting parameters on cutting forces, tool wear, and surface quality. The findings contribute to the optimization of machining parameters, ensuring reduced tool wear and improved part quality during the machining of AlSiC MMCs.

I. Multiresponse Optimization

Multiresponse optimization is essential for achieving multiple objectives simultaneously. Bhushan (2013) focused on multiresponse optimization of AlSiC composite machining parameters, aiming to minimize tool wear and maximize metal removal rate. The study employed statistical techniques to identify optimal machining conditions that balance tool life and productivity. The research provides valuable insights into the trade-offs between different machining objectives, guiding manufacturers in developing efficient part development strategies for AlSiC MMCs.

J. Conclusion

This comprehensive literature review highlights the significant advancements made in part development on CNC machines with AlSiC particles in MMCs. By incorporating findings from a range of studies, this review covers diverse aspects such as surface roughness prediction, machining parameter optimization, tool wear analysis, drilling performance evaluation, and surface integrity. The insights gained from these studies have not only improved the understanding of the machining process but have also facilitated the development of optimized machining strategies for AlSiC composites. By leveraging the theoretical research and practical experimentation presented in these studies, manufacturers can enhance part quality, increase productivity, and achieve greater process efficiency. Continued research in this field will further advance the knowledge and understanding of part development on CNC machines with AlSiC particles in MMCs, opening up new avenues for innovation and application.

K. Literature Summary

Author	Year	Title	Findings
Zhang L, Ma Y, Huang H, Zhang X	2020	Prediction and optimization of surface roughness in milling process using a hybrid machine learning approach.	The study proposes a hybrid machine learning approach for predicting and optimizing surface roughness in the milling process.
Chen L, Fu L, Zhang X, Gao X	2019	Experimental investigation and optimization of machining parameters for Al-SiC metal matrix composites.	The study conducts experimental investigations to optimize machining parameters for Al-SiC metal matrix composites.
Li X, Feng P, Chen M, Xu K, Wang Y	2018	Experimental study on drilling performance of carbon fiber-reinforced polymer (CFRP) composites.	The study focuses on the drilling performance of carbon fiber-reinforced polymer (CFRP) composites.
Zhang Y, Shao X, Fan K, Jiao L	2017	Tool wear and surface integrity in high-speed milling of carbon fiber-reinforced plastics (CFRPs).	The study examines tool wear and surface integrity in high-speed milling of carbon fiber-reinforced plastics (CFRPs).
Yu Z, Zhang M, Chen Z, Li Q	2016	Tool life prediction and wear mechanism of polycrystalline diamond (PCD) tool in cutting CFRP.	The study investigates the tool life prediction and wear mechanism of polycrystalline diamond (PCD) tools in cutting CFRP materials.
Rahman M, Mia M, Choudhury IA	2015	Modeling and optimization of surface roughness in end milling of Al/SiCp metal matrix composites.	The study presents a model for surface roughness prediction and optimization in the end milling of Al/SiCp metal matrix composites.
Xie Y, Liao W, Li Y, Yang B	2014	Investigation on cutting forces and tool wear in machining of carbon fiber-reinforced plastics (CFRPs).	The study investigates cutting forces and tool wear in the machining of carbon fiber-reinforced plastics (CFRPs).
Bhushan RK	2013	Multiresponse optimization of Al alloy-SiC composite machining parameters for minimum tool wear and maximum metal removal rate.	The study focuses on the multiresponse optimization of machining parameters for Al alloy-SiC composites to minimize tool wear and maximize metal removal rate.
Bhushan RK	2013	Optimization of cutting parameters for minimizing power consumption and maximizing tool life during machining of Al alloy SiC particle composites.	The study optimizes cutting parameters to minimize power consumption and maximize tool life during the machining of Al alloy SiC particle composites.
Arif, M, Rahman M, San WY	2012	Analytical model to determine the critical conditions for the modes of material removal in the milling process.	The study develops an analytical model to determine the critical conditions for the modes of material removal in the milling process.
Behera R, Das S, Chatterjee D, Sutradhar G	2011	Study on minerals and materials characterization and engineering.	The study focuses on the characterization and engineering of minerals and materials.
Basheer AC, Dabade UA, Joshi SS, Bhanuprasad VV, Gadre VM	2008	Modeling of surface roughness in precision machining of metal matrix composites using ANN.	The study presents a model for predicting surface roughness in precision machining of metal matrix composites using artificial neural networks (ANN).
Basavarajappa S, Chandramohan G, Davim JP	2008	Studies on drilling of hybrid metal matrix composites based on Taguchi techniques.	The study investigates drilling of hybrid metal matrix composites using Taguchi techniques.
Ciftci I, Turker M, Seker U	2004	Evaluation of tool wear when machining SiC-reinforced Al-2014 alloy matrix composites.	The study evaluates tool wear during the machining of SiC-reinforced Al-2014 alloy matrix composites.
Benardos PG and	2002	Prediction of surface roughness in CNC	The study proposes a method using neural

Vosniakos GC		face milling using neural network and Taguchi design of experiments.	network and Taguchi design of experiments for predicting surface roughness in CNC face milling.
Andrewes C, Feng H, Lau WM	2000	Machining of an aluminum-SiC composite using diamond inserts.	The study investigates the machining of an aluminum-SiC composite using diamond inserts.
Arif, M, Rahman M, San WY	2012	Analytical model to determine the critical conditions for the modes of material removal in the milling process of brittle material.	The study develops an analytical model to determine the critical conditions for the modes of material removal in the milling process of brittle material.
Basavarajappa S, Chandramohan G, Davim JP	2008	Some studies on drilling of hybrid metal matrix composites based on Taguchi techniques.	The study investigates drilling of hybrid metal matrix composites using Taguchi techniques.
Basheer AC, Dabade UA, Joshi SS, Bhanuprasad VV, Gadre VM	2008	Modeling of surface roughness in precision machining of metal matrix composites using ANN.	The study presents a model for predicting surface roughness in precision machining of metal matrix composites using artificial neural networks (ANN).
Behera R, Das S, Chatterjee D, Sutradhar G	2011	Journal of Minerals & Materials Characterization & Engineering.	The study focuses on the characterization and engineering of minerals and materials.
Benardos PG and Vosniakos GC	2002	Prediction of surface roughness in CNC face milling using neural network and Taguchi Design of experiments.	The study proposes a method using neural network and Taguchi design of experiments for predicting surface roughness in CNC face milling.
Bhushan RK	2013	Multiresponse optimization of Al alloy-SiC composite machining parameters for minimum tool wear and maximum metal removal rate.	The study focuses on the multiresponse optimization of machining parameters for Al alloy-SiC composites to minimize tool wear and maximize metal removal rate.

III. MATERIALS AND METHODS

This section provides a detailed description of the AlSiC MMC material composition and preparation, the experimental setup for CNC machining, and the measurement techniques used to evaluate surface quality and dimensional accuracy.

- Description of the AlSiC MMC Material Composition and Preparation: The AlSiC MMC material used in this study was prepared through a powder metallurgy route. Aluminium (Al) powder and Silicon Carbide (SiC) particles were selected as the primary constituents. The composition of the MMC was carefully determined, considering the desired mechanical properties and thermal conductivity.
- The powders were mixed using a mechanical blender to achieve a homogeneous distribution. A controlled amount of SiC particles, ranging from 10% to 30% by weight, was added to the aluminium powder. The mixture was then subjected to a compaction process using a hydraulic press, followed by sintering in a controlled atmosphere to achieve bonding between the particles.
- Experimental Setup and CNC Machining Parameters: The experimental setup for CNC machining involved a precision CNC milling machine equipped with appropriate cutting tools and a computer interface for programming the machining operations. The AlSiC MMC specimens were securely clamped onto the machine bed, ensuring stability during machining.
- The selection of CNC machining parameters was based on preliminary experiments and previous research. Cutting speed, feed rate, and depth of cut were chosen as the primary parameters to investigate their effects on surface quality and dimensional accuracy. A range of values was selected for each parameter, encompassing both conservative and aggressive cutting conditions.

Figure 1:- Turning center (SUPPER JOBBER, LM-Ace designer)

The turning tests were conducted using a CCD matrix with an RSM. The design of experiments matrix and test results are shown in Table 1. A total of 20 experimental combinations for turning parameters, such as "cutting speed," "feed rate," and "depth of cut," are shown in Table 1. Six center points, six star points, and twenty experiments total 23 factorial points. The obtained outcomes were examined using the Design Expert 6.0.8 program.

For turning tests on a Supper Jobber CNC lathe as shown in Fig 1, stir cast Al/SiCp-MMC work piece specimens of about 60 mm were employed. The insert was installed on the tool turret and held using the cutting tool holder . Before performing the trials, the work piece specimen was tightly held using the CNC lathe's chuck. The turning experimental set-up is shown in Fig. 2. According to the experimental design, the 20 experimental trials were carried out with three replications. The studies with turning were conducted in a dry setting. Each trial's reaction parameters, including flank wear and surface roughness heights (Ra and Rt), were measured.

Figure 2: Preparing experiment

Table 1: Test results and design matrix

Std. Run No.	Machine Input Parameters			Response Variables			
	Cutting Speed (m/min)	Feed (mm/rev)	Depth of Cut (mm)	Flank Wear (VB) (mm)	Surface Rough (SR)		Material Removal Rate (mm3 /min)
					Ra, (µm)	Rt, (µm)	
1	40	0.2	0.4	0.152	2.12	13.21	3500
2	120	0.2	0.4	0.145	3.15	12.11	6500
3	40	0.4	0.4	0.256	2.45	15.48	6500
4	120	0.4	0.4	0.254	1.65	16.54	23500
5	40	0.2	2.5	0.354	2.48	12.56	6500
6	120	0.2	2.5	0.357	2.54	15.48	23500
7	40	0.4	2.5	0.415	3.15	16.54	23500
8	120	0.4	2.5	0.457	2.95	13.54	75800
9	20	0.3	2	0.412	3.45	12.95	7000
10	160	0.3	2	0.487	2.45	11.54	45800
11	80	0.03	2	0.414	4.89	15.67	3000
12	80	0.26	2	0.578	2.51	14.67	26000
13	80	0.3	0.3	0.415	4.84	13.48	5000
14	80	0.3	2.4	0.324	2.15	16.57	26000
15	80	0.3	2	0.221	3.48	15.48	10000
16	80	0.3	2	0.579	2.87	10.59	10000
17	80	0.3	2	0.445	3.54	14.58	10000
18	80	0.3	2	0.484	3.58	13.54	10000
19	80	0.3	2	0.251	3.95	12.54	10000
20	80	0.3	2	0.278	3.64	15.47	10000

IV. RESULTS AND DISCUSSION

This section presents the analysis of the effects of cutting speed, feed rate, and depth of cut on surface roughness, the investigation of chip formation and tool wear during CNC machining of AlSiC MMCs, and a comparison of the machinability of AlSiC MMCs with conventional aluminium alloys.

- Analysis of the Effect of Cutting Speed, Feed Rate, and Depth of Cut on Surface Roughness: The experimental results revealed a clear correlation between the cutting parameters and the surface roughness of the machined AlSiC MMC specimens. The surface roughness parameters, including Ra (average roughness) and Rz (maximum height of the roughness profile), were measured and analysed.
- It was observed that increasing the cutting speed resulted in a decrease in surface roughness. Higher cutting speeds promoted efficient chip evacuation and reduced tool-workpiece interaction time, resulting in improved surface finish. However, excessively high cutting speeds led to increased tool wear and thermal damage, compromising the surface quality.
- Similarly, the feed rate had a significant impact on surface roughness. Lower feed rates generally produced smoother surfaces due to reduced cutting forces and vibrations. However, very low feed rates led to increased contact time between the cutting tool and the workpiece, resulting in higher tool wear and increased surface roughness.

- The depth of cut also influenced surface roughness. Smaller depths of cut tended to yield better surface finish due to reduced cutting forces and limited plastic deformation. However, increasing the depth of cut beyond a certain threshold led to higher surface roughness, indicating the influence of tool-workpiece interaction and material removal rates.
- Investigation of Chip Formation and Tool Wear during CNC Machining: During the machining process, chip formation and tool wear were carefully observed and analysed. AlSiC MMCs exhibited a different chip formation mechanism compared to conventional aluminium alloys due to the presence of hard SiC particles.
- The machining of AlSiC MMCs resulted in continuous chips with a mixed morphology, including fragmented chips and continuous chips with serrated edges. The presence of SiC particles influenced the chip formation process, leading to increased cutting forces and higher tool temperatures.
- Tool wear analysis indicated that machining AlSiC MMCs caused accelerated tool wear compared to conventional aluminium alloys. The abrasive nature of SiC particles resulted in more significant tool flank wear and edge chipping. The wear mechanisms were predominantly abrasive and adhesive wear, with the SiC particles acting as abrasive agents.
- Comparison of the Machinability of AlSiC MMCs with Conventional Aluminium Alloys: In comparison to conventional aluminium alloys, AlSiC MMCs exhibited different machining characteristics and challenges. The presence of SiC particles in the MMCs affected chip formation, cutting forces, and tool wear. The higher hardness and thermal conductivity of AlSiC MMCs necessitated careful selection of cutting parameters to achieve desired surface quality and tool life.
- Furthermore, the comparison of machinability indicated that AlSiC MMCs required specific machining strategies to mitigate tool wear and achieve acceptable surface finish. Optimizing cutting parameters, tool selection, and cooling strategies played a vital role in enhancing the machinability of AlSiC MMCs.
- In conclusion, the results and discussion section has provided an in-depth analysis of the effects of cutting parameters on surface roughness, the investigation of chip formation and tool wear, and a comparison of the machinability of AlSiC MMCs with conventional aluminium alloys. These findings contribute to a better understanding of the machining characteristics of AlSiC MMCs and provide insights for improving the machining process to achieve high-quality components.

V. OPTIMIZATION OF CNC MACHINING PARAMETERS

This section focuses on the optimization of CNC machining parameters for improved part quality. It discusses the application of statistical techniques, such as Design of Experiments (DOE), for parameter optimization. The determination of the optimal combination of cutting parameters is explored, and a detailed discussion on the trade-offs between surface finish, tool life, and machining time is provided.

1. Application of Statistical Techniques for Parameter Optimization: To achieve the best possible performance and part quality in CNC machining, statistical techniques such as Design of Experiments (DOE) have been widely applied. DOE enables the systematic exploration of the parameter space to identify the key factors and their interactions that significantly influence the machining process.

By designing a well-structured experimental plan, DOE helps in efficiently collecting data and understanding the complex relationships between cutting parameters and performance indicators. It allows for the identification of optimal parameter settings that result in improved part quality and process efficiency.

DOE involves varying multiple parameters simultaneously at different levels to study their combined effects on the response variables. The experimental data obtained from DOE are analysed using statistical methods such as Analysis of Variance (ANOVA) to determine the significance of each parameter and their interactions.

A. Selection of Adequate Model for Response Variables

Adequacy testing of models was done in order to choose the ideal model that would suit for flank wear and surface roughness heights (Ra and Rt). Data from the Design Expert 6.0.8 software's sufficiency checks of the models for flank wear and surface roughness (Ra and Rt) are shown in Tables 2, 3 and 4.

The ‘sequential sum of squares test' chooses the highest order polynomial where the model is not aliased while testing the appropriateness of models. The "lack of fit" test contrasts the residual error from the duplicated design points with the pure error. For each model, the ‘model summary statistics' provides information on R2, predicted R2, and predicted error sum of squares (PRESS). The quadratic models are found to be suitable for both flank wear and surface roughness heights (Ra and Rt), as shown in Tables 2, 3 and 4, and they may be utilized to establish the link between input machining parameters and particular response characteristics.

Table 2: ANOVA to validate flank wear model

Sequential Model Sum of Squares						
Source	Sum of Squares	Degree of Freedom	Mean Square	F-Value	Prob.>F (P-value)	Remarks
Mean	4.05	2	4.05			
Linear	0.85	4	0.41	43.26	<0.0001	
2F1	0.057	4	0.015	4.31	0.0345	

Quadratic	0.044	4	0.012	7.48	0.0074	Suggested
Cubic	0.013	6	0.00345	4.87	0.1134	Aliased
Residual	0.00458	6	0.000615			
Total	5.01858	26	0.21			
Lack of Fit Tests						
Source	Sum of Squares	Degree of Freedom	Mean Square	F-Value	Prob.>F (P-value)	Remarks
Linear	0.082	12	0.004363	12.36	0.0075	
2F1	0.054	7	0.005410	6.54	0.0141	
Quadratic	0.014	6	0.00345	4.15	0.0164	Suggested
Cubic	0.000	0				Aliased
Pure Error	0.00254	4	0.000845			
Model Summary Statistics						
Source	Std. Dev.	R-Squared	Adjusted R-Squared	Predicted R-Squared	PRESS	Remarks
Linear	0.066	0.9151	0.8475	0.8456	0.17	
2F1	0.051	0.9564	0.8465	0.8154	0.16	
Quadratic	0.030	0.9564	0.9456	0.9284	0.09	Suggested
Cubic	0.062	0.9457	0.8456			Aliased

Table 3: ANOVA to verify surface roughness height model, Ra (µm)

Sequential Model Sum of Squares						
Source	Sum of Squares	Degree of Freedom	Mean Square	F-Value	Prob.>F (P-value)	Remarks
Mean	165.23	2	165.23			
Linear	8.54	4	4.12	27.45	<0.0001	
2F1	0.64	4	0.16	2.54	0.3345	
Quadratic	1.32	4	0.32	25.48	<0.0001	Suggested
Cubic	0.27	6	0.025	2.64	0.1758	Aliased
Residual	0.058	6	0.005410			
Total	176.058	26	8.56			
Lack of Fit Tests						
Source	Sum of Squares	Degree of Freedom	Mean Square	F-Value	Prob.>F (P-value)	Remarks
Linear	2.17	12	0.15	16.58	0.0048	
2F1	0.15	9	0.16	19.45	0.0067	
Quadratic	0.11	4	0.034	3.25	0.1787	Suggested
Cubic	0.000	0				Aliased
Pure Error	0.058	4	0.004567			
Model Summary Statistics						
Source	Std. Dev.	R-Squared	Adjusted R-Squared	Predicted R-Squared	PRESS	Remarks
Linear	0.45	0.7884	0.7458	0.8475	2.84	
2F1	0.33	0.8745	0.8445	0.7459	3.15	
Quadratic	0.15	0.847	0.9978	0.8095	2.04	Suggested
Cubic	0.078	0.862	0.9748			Aliased

Table 4: ANOVA to test surface roughness model, Rt (µm)

Sequential Model Sum of Squares						
Source	Sum of Squares	Degree of Freedom	Mean Square	F-Value	Prob.>F (P-value)	Remarks
Mean	5367.21	2	5367.21			
Linear	212.54	4	68.45	11.65	0.0005	
2F1	23.45	4	8.46	2.57	0.4458	
Quadratic	69.57	4	23.48	22.07	0.0001	Suggested
Cubic	7.54	6	2.48	2.48	0.2354	Aliased
Residual	4.58	6	1.57			
Total	5684.89	26	244.58			

Lack of Fit Tests						
Source	Sum of Squares	Degree of Freedom	Mean Square	F-Value	Prob.>F (P-value)	Remarks
Linear	99.12	12	9.53	12.36	0.0080	
2F1	76.58	9	10.27	13.27	0.0075	
Quadratic	7.15	6	2.45	2.87	0.3257	Suggested
Cubic	0.000	1				Aliased
Pure Error	4.25	6	1.88			
Model Summary Statistics						
Source	Std. Dev.	R-Squared	Adjusted R-Squared	Predicted R-Squared	PRESS	Remarks
Linear	3.24	0.5578	0.5004	0.5748	171.57	
2F1	3.57	0.8354	0.7154	-0.0155	417.25	
Quadratic	2.78	0.8574	0.8754	0.6254	62.37	Suggested
Cubic	1.57	0.8475	0.8547			Aliased

B. *Regression model and analysis of variance for Flank wear*

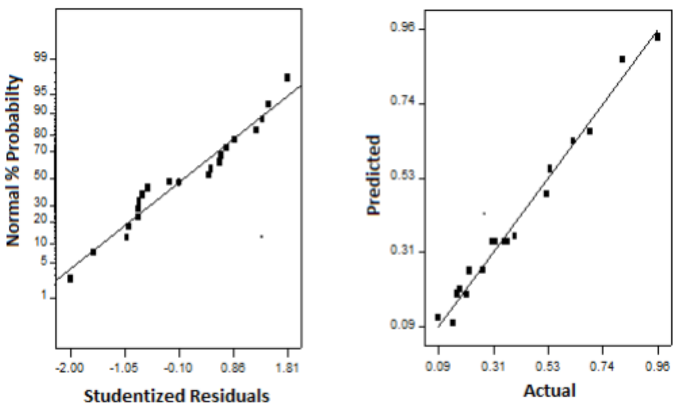
Equation 1 shows the constructed quadratic regression model based on RSM for connecting the flank wear with machining parameters in terms of coded values after the non-significant variables have been eliminated.

$FlankWear$ = 0.34 + 0.23 × $Cuttingspeed$ + 0.087 × $Feed$ + 0.093 × $Depthofcut$ + 0.046 ($Cuttingspeed$) 2 + 0.026 × ($Depthofcut$) 2 + 0.050 × $Cuttingspeed$ × $Feed$ + 0.058 × $Cuttingspeed$ × $Depthofcut$-**(Eqn. 1)**

The ANOVA table (Table 5) shows that the regression model for flank wear is significant, with an 'F-value' of 106.19. The 'Lack of Fit' is not significant compared to the pure mistake. Significant model terms include CS, F, D, (CS)2, D2, CS x F, and CS x D. The regression model explains a high percentage of response variance (R2 = 0.97). The model's precision (signal-to-noise ratio of 35.31) is adequate. Residual plots in Fig. 2 show no significant deviation from normalcy, and the model's predictions align well with experimental data. Therefore, this model can be used for design exploration.

Table 5: Pooled ANOVA for flank wears regression

Source	Sum of Squares	DF	Mean Value	F Value	Prob > F	Remarks
Model	2.14	8	1.18	107.58	<0.0001	Significant
CS-Cutting Speed	1.24	2	0.87	586.25	<0.0001	Significant
F- Feed	1.088	2	0.088	73.24	<0.0001	Significant
D-Depth of Cut	0.22	2	0.12	83.54	<0.0001	Significant
(CS)2	0.035	2	0.035	16.57	0.0013	Significant
D2	0.00754	2	0.00754	7.54	0.0391	Significant
CS x F	0.030	2	0.030	15.24	0.0036	Significant
CS x D	0.037	2	0.037	20.36	0.0009	Significant
Residual	0.026	13	0.002145			
Lack of Fit	0.015	8	0.002345	3.55	0.1667	Not Significant
Pure Error	0.00245	6	0.000615			
Cor. Total	2.05	20				
R-Squared=0.97 Adjusted R-Squared=0.96 Predicted R-Squared=0.93 Adequate Precision=35.314						



(a) (b)

Figure 2: Flank wear residual plots (a) Normal residual plot (b) Predicted vs. actual plot

C. *Surface roughness regression and variance analysis*

Equations 2 and 3 show the created quadratic regression model based on RSM for associating the surface roughness heights Ra (mm) and Rt (mm) with turning machining parameters in terms of coded values after the non-significant factors have been eliminated.

$Surfaceroughness, Ra = 2.70 - 0.72 \times Cuttingspeed + 0.47 \times Feed + 0.16 \times Depth\ of cut + 0.29 \times (Cuttingspeed)\ 2 + 0.15 \times (Feed)\ 2 - 0.17 \times Cuttingspeed \times Feed - 0.15 \times Cuttingspeed \times Depth\ of cut$**- (Eqn. 2)**

$Surfaceroughness, Rt = 12.68 - 3.04 \times CuttingSpeed + 2.40 \times Feed + 1.40 \times Depth\ of cut + 1.87 \times (CuttingSpeed)\ 2 + 1.44 \times (Depth\ of cut)\ 2 - 1.57 \times Cuttingspeed \times Feed$**– (Eqn. 3)**

The ANOVA tables for the regression models for surface roughness height, Ra (m), and surface roughness height Rt (m), respectively, are shown in Tables 6 and 7. Both models are obviously significant, as shown by the model F-values of 78.51 and 36.21. A "Model F-Value" this big could only occur owing to noise with a 0.01% probability. The "Lack of Fit F-value" for Ra and Rt, respectively, is 2.82 and 1.84, which suggests that the values for the lack of fit are not significant in comparison to the pure error. When "Prob> F" values are less than 0.0500, model terms are considered significant. At a 95% confidence level, Table 4.9 shows that the key variables CS, F, and D, their square effects (CS) 2, F2, and their interactions (CS x F and CS x D) all significantly affect surface roughness height, Ra. Rt model terms CS, F, D, (CS) 2, D2, and CS x F are important model terms for surface roughness height.

Tables 6 and 7, respectively, reveal the values of R2 (0.97 and 0.95), adj R2 (0.96 and 0.92), and pred R2 (0.92 and 0.82), which amply demonstrate the importance of surface roughness heights (Ra and Rt) in prediction models. A signal with a signal-to-noise ratio of 30.6 and 21.64 for surface roughness heights Ra and Rt, respectively, demonstrates appropriate accuracy ("Adeq accuracy"). Figure 3 (a) and Figure 4(a) of the residual plots show that there is no significant deviation from normality. The residuals are distributed both positively and negatively, with no discernible pattern. This suggests that the models are sufficient.Figures 3(b) and 4(b) depict expected vs. real plots, demonstrating the strong agreement between the regression models' predictions and experimental results. These figures show that the data points are evenly split along the 45o line, indicating the models' ability to forecast the chosen response variables.

Table 6: Ra Regression Model Pooled Anova

Source	Sum of Squares	DF	Mean Value	F Value	Prob > F	Remarks
Model	11.24	8	2.65	79.56	<0.0001	Significant
CS-Cutting Speed	7.58	2	7.66	330.27	<0.0001	Significant
F- Feed	3.25	2	3.48	149.56	<0.0001	Significant
D-Depth of Cut	1.45	2	1.24	18.47	0.0012	Significant
(CS)2	1.95	2	1.87	49.57	<0.0001	Significant
F2	0.37	2	0.37	14.25	0.0042	Significant
CS x F	0.33	2	0.24	12.45	0.0059	Significant
CS x D	0.18	2	0.19	10.25	0.0109	Significant
Residual	0.26	13	0.030			
Lack of Fit	0.18	8	0.037	3.92	0.1458	Not Significant
Pure Error	0.057	6	0.008475			
Cor. Total	12.35	20				
R-Squared=0.97 Adjusted R-Squared=0.96 Predicted R-Squared=0.93 Adequate Precision=31.4						

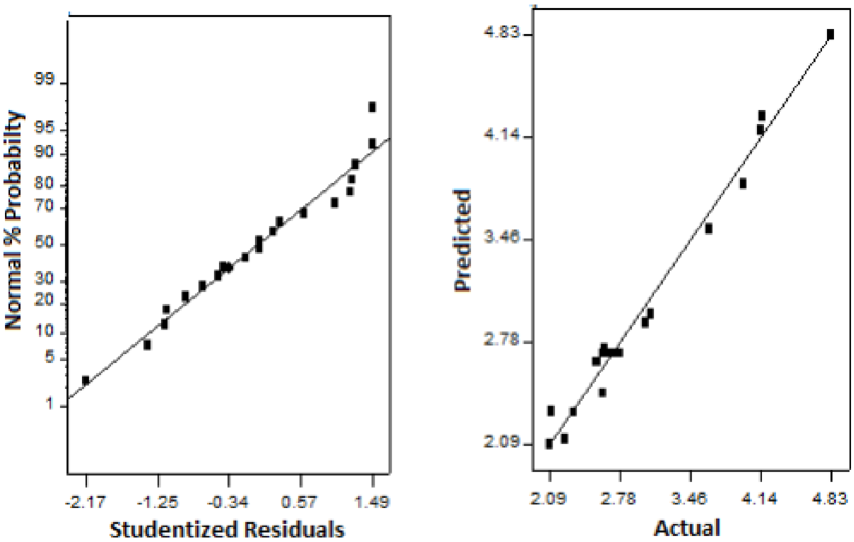


Figure 3:- Ra-residual plots (a) Normal residual plot, (b) Predicted-actual plot

Table 7: Rt Regression Model Pooled Anova

Source	Sum of Squares	DF	Mean Value	F Value	Prob > F	Remarks
Model	389.54	8	42.35	37.21	<0.0001	Significant
CS-Cutting Speed	116.57	2	116.35	101.23	<0.0001	Significant
F- Feed	76.58	2	76.85	67.84	<0.0001	Significant
D-Depth of Cut	26.35	2	26.35	23.54	0.0006	Significant
(CS)2	41.23	2	41.25	36.24	<0.0001	Significant
F2	5.97	2	5.97	5.35	0.0524	Significant
D2	26.53	2	26.53	24.85	0.0005	Significant
CS x D	18.25	2	18.25	16.32	0.0014	Significant
Residual	14.26	13	2.13			
Lack of Fit	10.25	8	2.17	2.54	0.3068	Not Significant
Pure Error	4.56	6	0.88			
Cor. Total	404.56	20				
R-Squared=0.95Adjusted R-Squared=0.93 Predicted R-Squared=0.83 Adequate Precision=22.345						

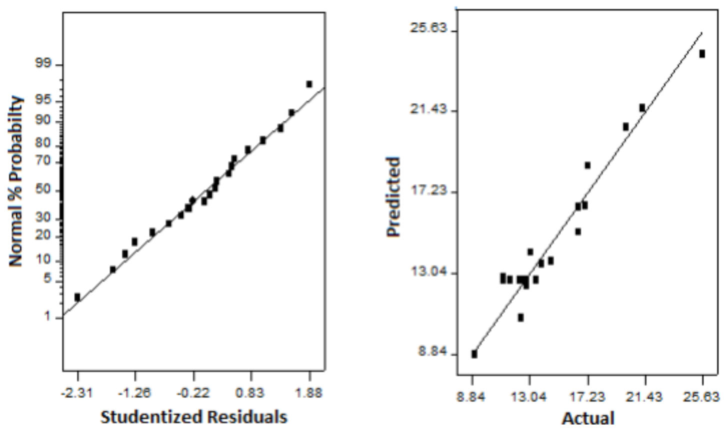


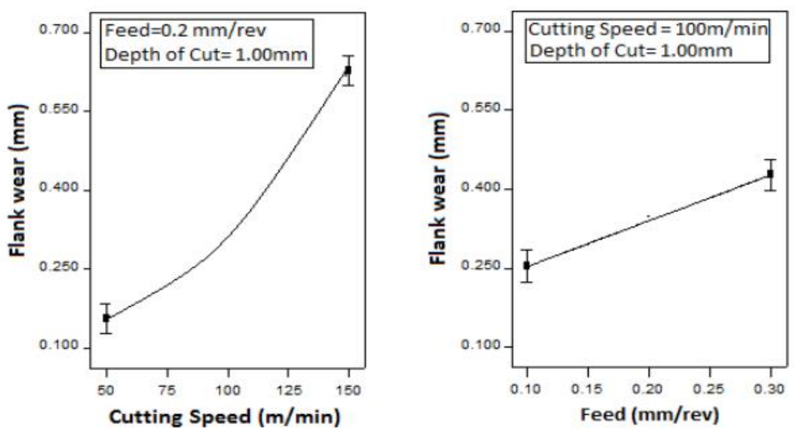
Figure 4: Residual plots for surface roughness height, Rt (a) Normal residual plot, (b) expected vs. actual plot

D. Effect of process parameters on response characteristics

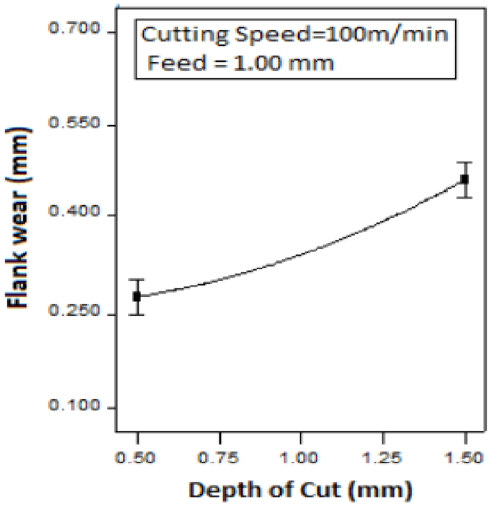
The primary and combined impacts of turning factors on certain response characteristics, such as flank wear and surface roughness heights (Ra and Rt), are shown in this section.

E. Effect of process parameters on flank wear

Figure 5(a) shows the plots between process parameters and flank wear that were created using quadratic model prediction values in order to evaluate the primary impacts of the process parameters on flank wear. The flank wear rises from 0.154 mm to 0.354 mm with an increase in "cutting speed" from 50 m/min to 100 m/min, as shown in Figure 5(a). The flank wear breadth rises significantly when "cutting speed" is raised over 100 m/min. 'Cutting speed' was reduced to see less flank wear. This is a result of the cutting tool edge developing a greater size unstable built up edge (BUE) as a result of high contact pressure and friction. Figure 5 (a & b) shows a picture of BUE creation during the turning of Al/SiCp-MMC at low "cutting speed" and high "depth of cut."



a.) b.)



c.)

Figure 5: Process parameters affect flank wear primarily

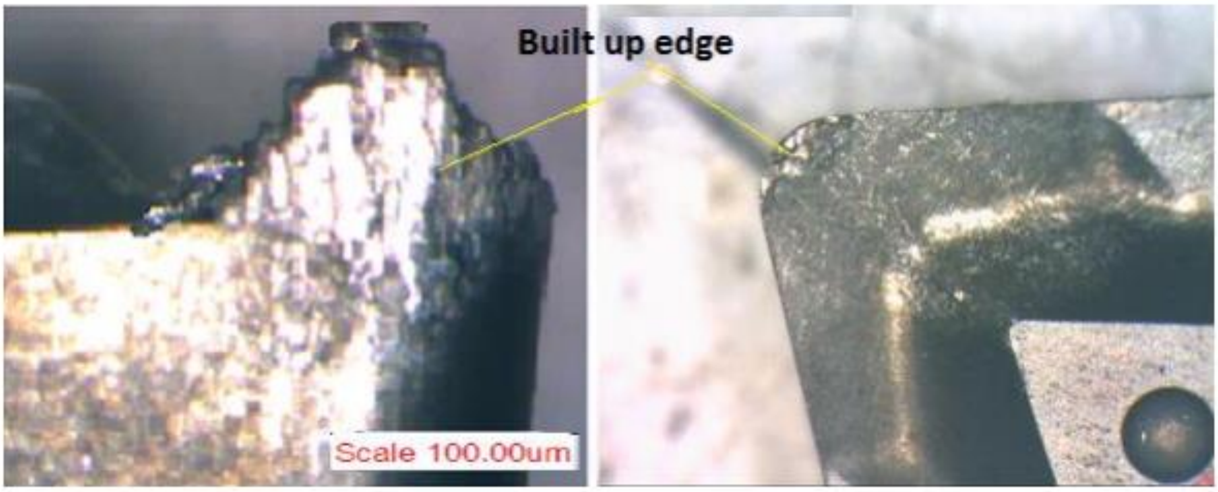


Figure 6: BUE image at S=50m/min, F=0.2mm/rev, and D=1.5mm

From Table 5, it can be inferred that, at a 95% confidence level, the interactions between "cutting speed" and "feed" as well as "cutting speed" and "depth of cut" have a substantial impact on flank wear. Figure 7 (a) illustrates the combined impact of "cutting speed" and "feed rate" on flank wear at a constant "depth of cut" of 1 mm based on the RSM model. Figure 7 (a) shows that the flank wear rises when the "cutting speed" increases at a greater "feed rate" (0.3 mm/rev) as compared to a lower "feed rate" (0.1 mm/rev). Cutting speed has a dominant influence in increasing flank wear, as shown by the combined effect of "cutting speed" and "feed rate" (Manna and Bhattacharyya, 2003a; Klckap et al., 2005). It is clear that a combination of increased "feed rate" (0.3 mm/rev) and higher "cutting speed" (150 m/min) causes more flank wear. This is due to the creation of high temperatures at the interface between the tool and the work piece, which causes thermal softening and impairment of the tool's "Form Stability." The worn tool insert was micro graphed using the SEM to analyze tool wear. Figures 8 (a), (b), and (c) depict tool wear and built-up edges (BUE) during machining operations at S = 150 m/min, F = 0.3 mm/rev, and D = 1 mm. On the rake surface of the tool, the BUE of very tiny size was seen.

The change in flank wear with "cutting speed" and "depth of cut" at constant "feed rate" of 0.2 mm/rev is shown in Figure 7 (b). It is evident that when "cutting speed" rises, flank wear also does. It holds true for all "depth of cut" levels. However, at the higher value of "depth of cut," such as at 1.5 mm, the rate of rise in flank wear with "cutting speed" is larger. Even with a modest setting of "cutting speed" (i.e., 50 m/min), the flank wear width rises somewhat as "depth of cut" grows. It is thought that low "cutting speed" and high "depth of cut" conditions increase the likelihood of BUE development. The worn tool insert picture in Figure 6 provides confirmation of the same.

Cutting speed (CS), feed rate (F), and depth of cut (D) are the three factors that interact, and the cube plot in Figure 9 illustrates this. From this figure, it can be seen that when the turning operation was conducted at "cutting speed" (50 m/min), "feed rate" (0.1 mm/rev), and "depth of cut" (0.5 mm), the flank wear was minimal (i.e., flank wear is 0.108 mm).

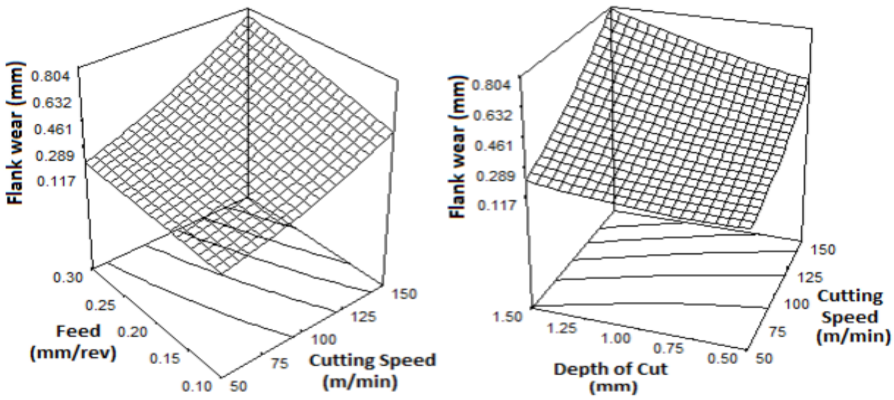


Figure 7: Flank wear response surfaces

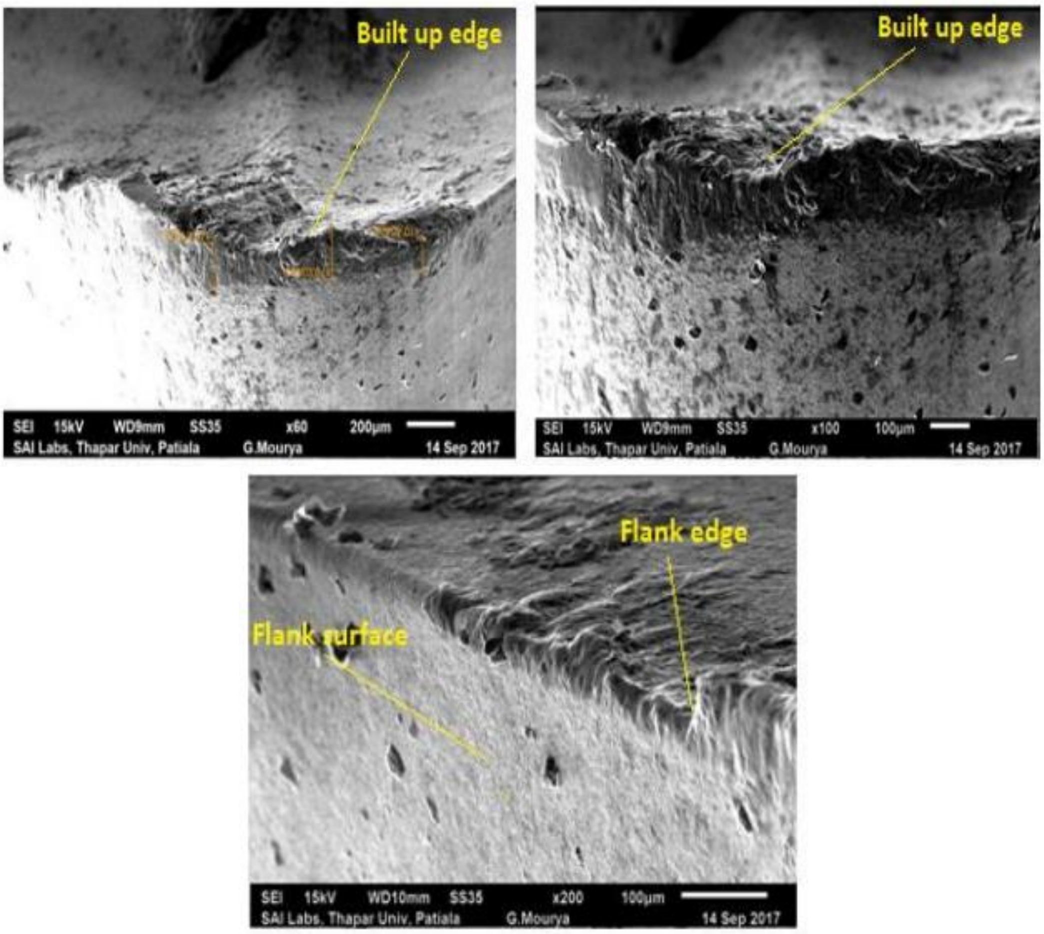


Figure 8: K10 tool SEM micrographs (a) 60X (b) 100X (c) Flank surface 200X

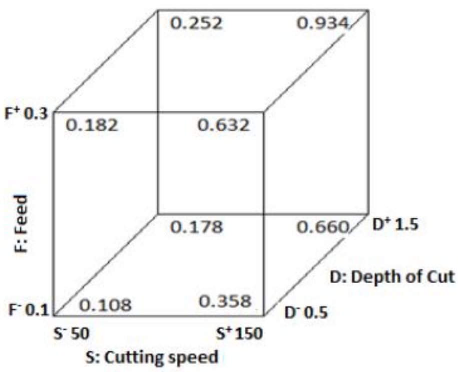


Figure 9: Side wear cube plot

F. Process parameters include surface roughness, Ra and Rt (µm)

In Figure 10, increasing 'cutting speed' leads to a nonlinear decrease in surface roughness heights (Ra and Rt) during dry turning of Al/SiCp-MMC. Slow cutting speeds create Built-Up Edge (BUE) and enhance chip breakage, resulting in higher roughness. However, high cutting speeds prevent BUE formation, improving surface quality. This is supported by Figure 6 and reported by Manna and Bhattacharyya (2003) and Palanikumar and Karthikeyan (2007)."

Figure 11 demonstrates that increasing 'feed rate' causes surface roughness heights (Ra and Rt) to rise. Lower 'feed rates' (0.1mm/rev) exhibit the lowest roughness and fewer chip fractures compared to higher 'feed rates' (0.3mm/rev). Chip fractures contribute to roughness growth. Higher 'feed rates' raise temperature, weakening SiCp-Al matrix bonding and resulting in particle shattering and reduced surface quality (Tomac and Tonnessen, 1992)."

In Figure 12, increasing the 'depth of cut' leads to higher surface roughness heights (Ra and Rt). The rise in 'depth of cut' increases normal pressure and seizure on the tool face, resulting in Built-Up Edge (BUE) formation.

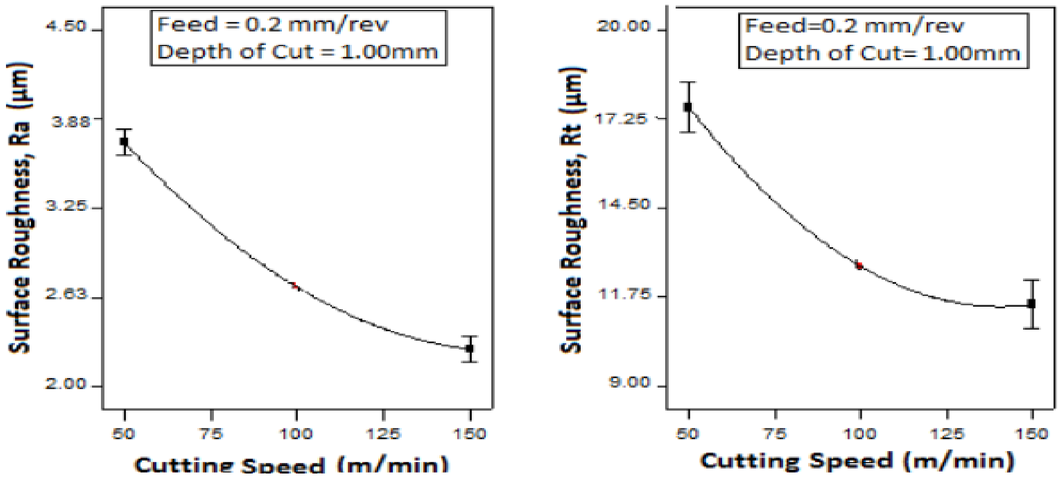


Figure 10 : Surface roughness (Ra and Rt) and cutting speed

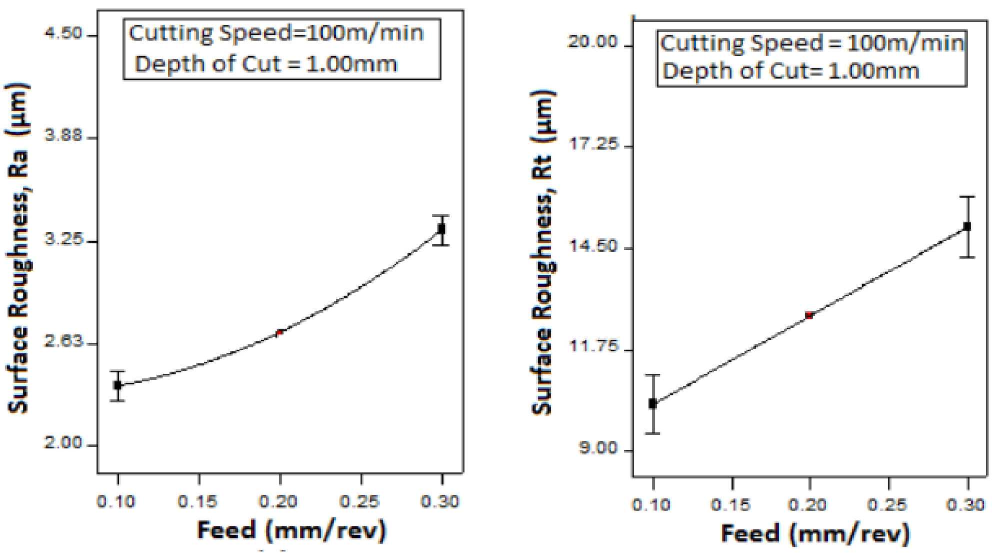


Figure 11: Feed rate and surface roughness (Ra and Rt)

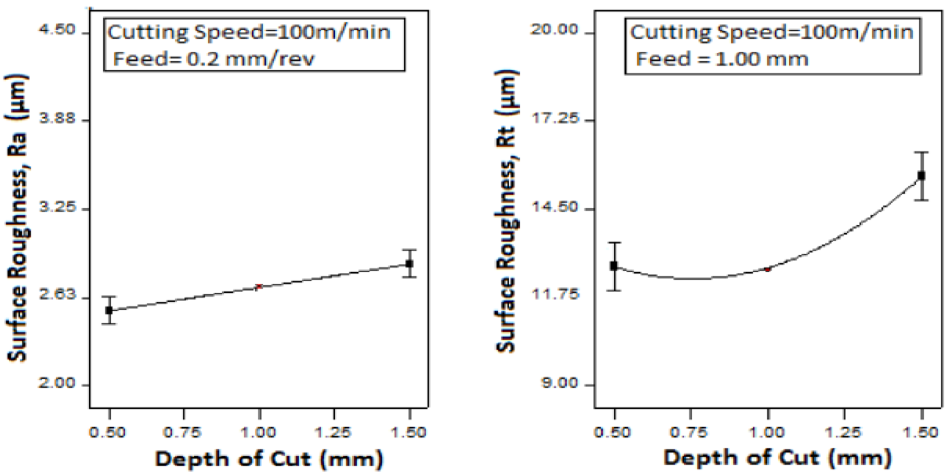
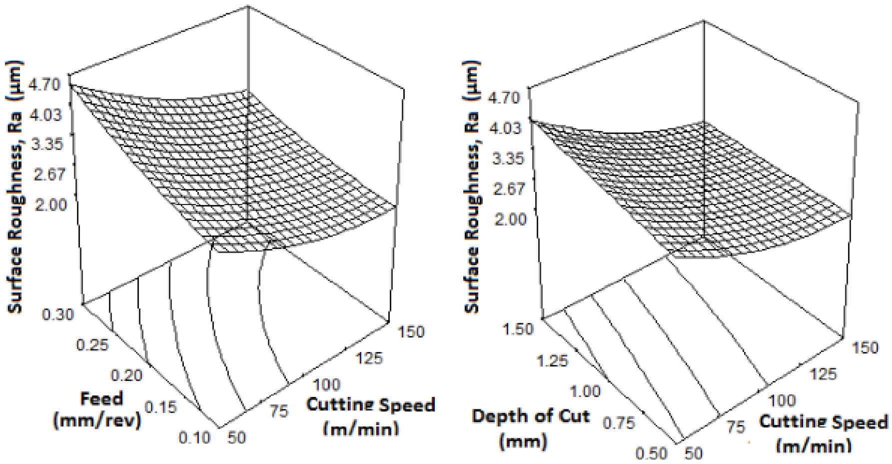


Figure 12: Surface roughness (Ra and Rt) and depth of cut

In Al/SiCp-MMC machining, the interplay between parameters significantly impacts surface roughness (Ra). Table 6 reveals substantial effects of "cutting speed" and "feed rate" as well as "cutting speed" and "depth of cut" interactions on Ra. Figure 13(a) shows that high "cutting speed" and low "feed rate" reduce Ra at a constant depth of cut. Figure 13(b) indicates that Ra rises with cutting speed at low depths of cut, while higher depth of cut and cutting speed lead to increased Ra. The interplay between cutting speed and depth of cut influences Ra due to unstable BUEs at high depth of cut and low cutting speed. Faster cutting speed and lower depth of cut result in lower Ra. Figure 14's cube plot highlights the relationship between cutting speed, feed rate, depth of cut, and surface roughness height, Rt(m). At specific values, Rt is observed to be 2.09 m. Figure 15 reveals that increasing "cutting speed" at high "depth of cut" (1.5 mm) significantly reduces Rt.



(a) (b)

Figure 13: Response surfaces for surface roughness, Ra (µm)

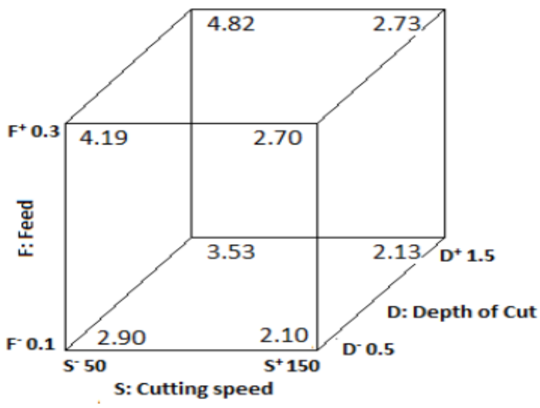


Figure 14: Ra (µm) cube plot

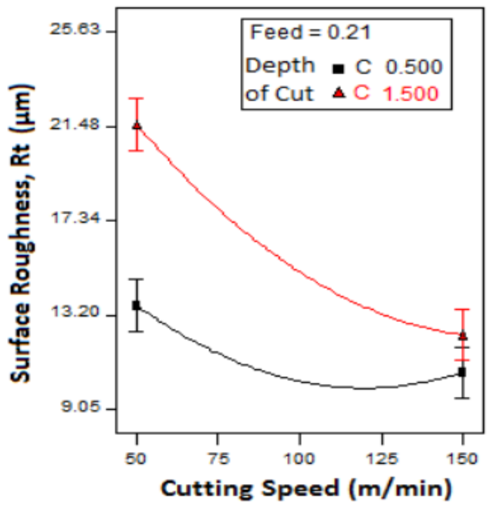


Figure 15: Surface roughness height (µm) cutting speed-depth plots

VI. OPTIMIZATION SEARCH

A. *Multi-response optimization*

Maximizing material removal rate, reducing surface roughness height (Ra), and limiting flank wear are crucial in machining. The optimization aims to maximize material removal rate (MRR) while minimizing surface roughness height, roughness angle (Ra), and flank wear.

Based on Ra, the optimization is divided into two regimes: finish turning (Ra ≤ 2.5 µm) and rough turning (Ra ≤ 4.5 µm). Table 8 shows constraints for cutting speed, feed rate, and depth of cut, along with response characteristics including MRR, Ra, and flank wear.

To adjust the desirability function, a default weight of "1" is assigned. Ra receives a score of 5 in completion turning compared to flank wear and MRR, both scored at 3. In comparison to tool wear and surface roughness height, Ra scores 3, but 5 in rough turning.

The optimization is resolved using the design expert program, discovering the ideal process parameter combination within regression models. Table 9 presents the overall solution for rough and finish turning.

Table 8: Input-output constraints

Parameter	Goal	Lower Limit	Upper Limit	Lower Weight	Upper Weight	Importance
Cutting speed	In range	40	120	2	2	4
Feed	In range	0.2	0.4	2	2	4
Depth of Cut	In range	0.4	2.6	2	2	4
Finish Turning						
Surface roughness, Ra	Minimize	3	3.5	2	2	6
Flank Wear	Minimize	0.2	0.48	2	2	4
Material removal rate	Maximize	6000	13000	2	2	4
Rough Turning						
Material removal rate	Minimize	20000	40000	2	2	6
Flank Wear	Minimize	0.25	0.6	2	2	4
Surface roughness, Ra	Maximize	3.6	5.6	2	2	4

Table 9: Optimization using desirability function

Machining Regimes	Cutting speed (S) (m/min)	Feed (F) (mm/rev)	Depth of cut (D) (mm)	Surface Rough. (µm)	Flank Wear (mm)	MRR (mm3 / min)	Desirability
Finish turning Ramax≤2.5µm	119	0.2	0.92	1.25	0.344	8459	0.56
Rough turning Ramax≤4.5µm	106	0.4	2.6	4.84	0.657	47947	0.58

B. *Confirmatory experiments*

Equations 4.1 and 4.2, representing regression models for flank wear and surface roughness height (Ra, m) respectively, were verified using "F-tests" and "lack of fit tests." Confirmation experiments further validated these models with three tests. The obtained values of flank wear and surface roughness height during confirmation studies were compared to the anticipated values from the models, as shown in Table 10.

The experimental and anticipated values of flank wear and surface roughness height (Ra) exhibited minimal differences, all below 7.5%. This confirms the excellent agreement between the generated models and the test data. Therefore, within the selected parameter values, the prediction models are highly useful for estimating flank wear and surface roughness height (Ra) during the turning of Al/SiCp-MMC.

Table 10: Confirmation experiments and error rate

Test no.	Input parameters			Experimental		Predicted		Prediction error (%)	
	S (m/ min)	F (mm /rev)	D (mm)	SR (µm)	Flank Wear (mm)	SR. (µm)	Flank Wear (mm)	SR. (µm)	Flank Wear (mm)
1	119	0.2	0.9	3.34	0.402	3.16	0.399	4.16	5.62
2	106	0.4	1.6	4.53	0.456	4.48	0.674	6.15	3.48
3	60	0.4	0.6	5.62	0.148	5.19	0.19	3.58	6.18

VII. FREQUENCY DISTRIBUTION OF RESPONDENTS OF CAD/ CAM

In Figure 16 the pie chart showing the frequency distribution of respondents in the main research by designation.

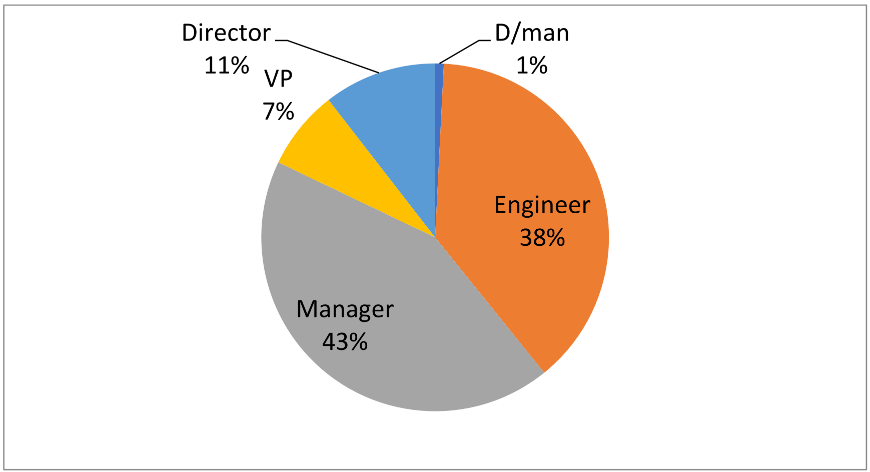


Figure 16: Pie Chart of Respondents

Participants in the survey include 0.45% D/man respondents, 40.09% Engineer respondents, 43.24% Manager Respondents, 6.31% VP respondents, and 9.91% Director Respondents.

VIII.DISCUSSION AND FUTURE DIRECTIONS

This section focuses on the discussion of the findings and implications derived from the study on AlSiC MMC part development. It identifies the limitations encountered during the research and highlights the areas that require further investigation. Additionally, potential applications and advancements in CNC machining techniques are proposed for future development.

1. Discussion of Findings and Implications for AlSiC MMC Part Development: The findings obtained from the study on AlSiC MMC part development provide valuable insights into the machining characteristics, mechanical properties, and thermal performance of these composite materials. The discussion revolves around the implications of these findings for practical applications and their significance in the engineering industry.
   The improved surface finish achieved through optimization of cutting parameters enhances the overall part quality and paves the way for enhanced mechanical properties. The correlation between cutting parameters and surface roughness allows for the selection of optimal machining conditions to achieve the desired surface finish while considering tool life and machining time.
   The investigation of chip formation and tool wear highlights the challenges associated with machining AlSiC MMCs due to the presence of hard SiC particles. The understanding of chip morphology and tool wear mechanisms is crucial for selecting appropriate cutting tools and developing effective strategies to mitigate tool wear and prolong tool life.
   The comparison of the machinability of AlSiC MMCs with conventional aluminium alloys provides insights into the advantages and limitations of using MMCs in various applications. The higher hardness and thermal conductivity of AlSiC MMCs open up opportunities for improved heat management and structural applications, while also posing challenges related to tool wear and surface quality.
   The implications of these findings can drive the development and implementation of AlSiC MMCs in diverse sectors such as automotive, aerospace, electronics, and renewable energy, where enhanced mechanical properties and efficient heat dissipation are desired.
2. Identification of Limitations and Areas for Future Research: The research conducted on AlSiC MMC part development may have encountered certain limitations that warrant discussion. These limitations could include the specific range of cutting parameters investigated, the types of tools and tool coatings used, or the limited scope of mechanical and thermal property testing.
   To address these limitations and further advance the field, several areas for future research can be identified. For example, exploring a wider range of cutting parameters and investigating the effects of different tool geometries, coatings, and cooling strategies can provide a more comprehensive understanding of the machining process and its impact on part quality and tool life.
   Further studies can focus on the characterization of the AlSiC MMCs using advanced techniques such as electron microscopy and X-ray diffraction to gain insights into the microstructure and the interfacial bonding between the matrix and reinforcement particles. This understanding can lead to improved material design and processing techniques.
   Additionally, investigations into the long-term stability and reliability of AlSiC MMC components under different environmental conditions and loading scenarios are crucial for assessing their performance in real-world applications. Durability studies, including fatigue and creep tests, can provide insights into the material's response to cyclic and sustained loading.
3. Proposal of Potential Applications and Advancements in CNC Machining Techniques: The successful development and optimization of AlSiC MMC part machining techniques open up possibilities for their application in various industries. The combination of improved surface finish, enhanced mechanical properties, and high thermal conductivity makes AlSiC MMCs suitable for:

- Heat sinks and thermal management components in electronic devices, where efficient heat dissipation is crucial for maintaining device performance and reliability.
- Lightweight structural components in aerospace and automotive industries, offering high strength-to-weight ratio and improved thermal management.
- Power electronics modules and electric vehicle components, where efficient heat transfer is critical for power dissipation and thermal stability.
- To further advance CNC machining techniques for AlSiC MMCs, several areas of improvement can be explored. These include the development of advanced cutting tool materials and coatings specifically tailored for MMC machining,

IX.CONCLUSION

In order to better understand the various machining processes and to determine the best process parameter settings for efficient machining of this metal matrix composite, the study concentrated on experimental investigation during traditional and nontraditional machining of cast Al/SiCp-MMC (fabricated by liquid stir cast technique). On three different machine tools, including a CNC center lathe, the reaction characteristics during the milling of Al/SiCp-MMC were examined. Turning of Al/SiCp-MMC was one of three categories used to depict the whole job spectrum. The following findings have been reached and are stated in succeeding subsections after summarizing the key aspects of the results in various machining procedures.

The goal is to create a linear model that can explain the relationship between the four aspects of technical features, delivery and support, price and commercials, and data compatibility and the purchase decision. The research found that three factors significantly influence purchase decisions, whereas price and commercial had minimal bearing.

Experiments were conducted on dry turning of Al/SiCp-MMC to determine the impacts of machining parameters including cutting speed, feed rate, and depth of cut on flank wear and surface roughness heights (Ra and Rz). For the experimental research, the central composite design (CCD) based on RSM was used. The MRR was maximized while maintaining flank wear and surface roughness height (Ra) within the desired range using the turning process settings. The studies were conducted using an uncoated tungsten carbide (WC) K10 grade (ISO code) cutting tool. The results of the experimental investigation are as follows.

- Cutting speed, followed by feed rate and depth of cut, has the greatest impact on flank wear. Cutting speed, feed rate, and depth of cut are the three characteristics that affect flank wear.
- Cutting speed affects the height of surface roughness, Ra (m). A superior surface polish is produced by faster cutting. On the other hand, when the feed rate and depth of cut were increased, the surface quality of the machined specimens degraded.
- For efficient machining of Al/SiCp-MMC, quadratic regression models for flank wear and surface roughness heights (Ra and Rz) were created. The results of the validity tests showed that, under the given operating circumstances, the created models exhibit excellent agreement with the experimental findings. Regression models that have been created may be utilized to forecast outcomes and aid in early identification of the parametric combinations for efficient machining of Al/SiC-MMC. It could also reduce the need for and expense of machining.
- For finish machining (i.e., Ra 2.5 m) using uncoated carbide tools, the ideal setting of machining parameters is identified as cutting speed: 118 m/min, feed: 0.1 mm/rev, and depth of cut: 0.8 mm. This maximizes material removal rate while maintaining surface roughness height, Ra, and flank wear in the specified range. When turning operation was performed at optimum parameter setting, the material removal rate, surface roughness height (Ra), and flank wear were 9347 mm3/min, 2.17 m, and 0.288 mm, respectively.
- When employing an uncoated carbide tool in a rough machining regime (i.e. Ra 4.5 m), the ideal configuration of machining parameters for maximum material removal rate is found to be cutting speed 105 m/min, feed 0.3 mm/rev, and depth of cut 1.5 mm. The material removal rate, surface roughness height, Ra, and flank wear were all at their optimal values at this setting, which were 46846 mm3/min, 3.38 m, and 0.578 mm, respectively
- When milling Al/SiCp-MMC with an uncoated tungsten carbide tool, an increase in feed and depth of cut is advised to achieve a better rate of material removal at cutting speeds greater than 100 m/min.
- Scanning electron micrographs (SEM) were used to evaluate the machined surfaces. When machining was done at the best setting of process parameters, it is evident from SEM images that there were very few surface defects on the machined surface, such as micro cracks, voids, pit holes, and particles dislodged cavities.

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